THE EFFECT OF OFF-FIELD ILLICIT ACTS ON PLAYER SALARIES IN THE NATIONAL FOOTBALL LEAGUE

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts

By

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May 2019

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Economics

Abstract

This paper examines the impact of crime on National Football League salaries. To evaluate the impact of crime, this paper uses on-field performance statistics from 2009-2018 seasons that was scraped from NFL.com and annual salary data from both USA Today NFL Salary Database and the Spotrac Salary Rankings Database. This study analyzes this data using an ordinary least squares regression model. It is important to note that the data for on-field statistics is not specific for each position used in this model and is limited due to the use of previously scraped data. In addition, it is important to note that there is an insignificant number of players who committed crimes in relation to the total number of players observed. Therefore, the regression results are insignificant. However, the results do suggest that if an NFL player commits a crime, it is likely that there will be no repercussions from the NFL regarding the player's salary.

KEYWORDS: (NFL, Domestic Violence, Crime, Salary)
JEL CODES: (J30, Z20, Z21, Z22)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

Molly Gillis

Signature

Thank you to everyone who helped me throughout this process. Mom and Dad, thank you for your continual support and encouragement. Professor Kevin Rask, thank you for your help merging the data. Professor Aju Fenn, thank you for your insight and guidance throughout the entire process, even when the outcomes were not as desired.

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Introduction

In the past decade, domestic violence has become a topic for discussion amongst fans and critics of the National Football League. Recent surveys have shown that 69% of Americans, 70% of NFL fans, and 73% of female fans believe that the NFL has a widespread epidemic of domestic violence (Leal, Gertz, & Piquero, 2015). Many critics claim that the NFL is too lenient in its punishment of players who have committed domestic violence crimes. Others say that it is in the nature of the game for these men to be violent which then carries over into their personal lives. Whatever the argument may be, the NFL still has major progress to make when it comes to the acknowledgement and punishment of those who have committed such crimes.

To understand the disciplinary system of the NFL, it is important to look at the specific crimes committed, and the level of punishment given for those crimes. Additionally, it is important to look at the impact that committing a crime has on the player. There are many areas committing a crime can affect a player, such as playing time, draft pick, salary, etc.; however, this study focuses specifically on the impact on the player's salary. This study continued previous research on the effect of crime on wage in the NFL by Ryan Nichols (2010). However, unlike previous studies, the initial focus of this study is the specific crime of domestic violence and how it effects NFL salaries.

Literature Review

Nichols (2010) examined the effects of illicit behaviors on player salaries in the National Football League. This study used an Ordinary Least Squares model to look at how on-field production statistics for three offensive positions and illicit behaviors affect salary determination. The results show that the effects vary depending on the different positions and crimes committed. Ultimately, the study showed that there are limited economic repercussions for players who commit illicit acts. This study will examine the impact of domestic violence and sexual misconduct on player's salaries, at the quarterback, running back, and wide receiver positions. In addition to looking at previous studies that analyze the effects of illicit behavior on NFL salaries, it is important to understand how the NFL personal conduct policy has changed in recent years and what events have caused those changes. This section begins by listing statistics of past conviction rates in the NFL, highlighting the need for policy change within the league. Next, this section will review the initial personal conduct policy that was implimented and will continue to discuss the changes that were made to the policy in an attempt to increase punishment and minimize crime. However, there are still weaknesses within the disciplinary system. Therefore, the next part of this section will describe the ongoing issues within the league's justice system, despite the updated personal conduct policy. Finally, this section will outline reccomendations to avert the inconsistencies in disciplinary actions.

When comparing the NFL crime rate to the general population, results indicate that there is no concrete proof that the NFL has a higher crime rate. However, crimes committed by a professional athlete receive more media coverage than those of the average person. In 1995, domestic violence cases involving athletes resulted in a 36 percent conviction rate, as compared to 77 percent for the general public (Robinson, 1998). From 2000-2014, under the NFL's personal conduct policy, a total of 48 players were punished. Out of those players, 88 percent received either a minimal suspension of one day or received no suspension at all (Brown, 2016). Many studies including Brown's 2010 study *When Pros Become Cons: Ending the NFL's History of Domestic Violence Leniency* and Kay-Phillips' 2016 study *Unnecessary Roughness: The NFL's History of Domestic Violence and the Need for Immediate Change* have found that the NFL still has major progress to make when it comes to the acknowledgement and punishment of those who have committed such crimes. The lack of punishment for domestic violence crimes is not only limited to the NFL, but is actually prevalent across many professional sports leagues, including Major League Baseball (MLB) and the National Basketball Association (NBA). Both Withers (2010) and Kim & Parlow (2009) discuss the different policies across these three leagues and ways to incorporate a more standard policy to eliminate discrepancies in disciplinary action.

In 1997, the Violent Crime Policy was created to outline the league's disciplinary stance towards players who committed crimes (Kay-Phillips, 2016). Another element of league enforcement of the personal conduct policy is in the Player Contract which contains the 'integrity of the game' provision. This provision permits the NFL Commissioner to discipline a player who "is guilty of any form of conduct reasonably judged by the League Commissioner to be detrimental to the League or professional football" (Kay-Phillips, 2016). This ensures that the commissioner has the authority to discipline players through fines, suspensions from playing without pay, and even to ban players from the league. This level of control led to a backlash from fans when NFL Commissioner Rodger Goodell essentially let NFL star Ray Rice off the hook after Rice was caught on camera beating his fiancé Janay Rice. The Rice incident eventually led to the implementation of an updated Personal Conduct Policy (PCP). The new Personal Conduct Policy allows for there to be additional investigation and initial disciplinary action taken by the NFL Special Counsel for Investigations (Brown, 2016). These two revisions distribute the power formerly given to the commissioner allowing for a more comprehensive view on the crime at hand. Furthermore, the updated PCP includes "the addition of a Conduct Committee, made up of NFL owners, to ensure that the policy remains current and consistent with the best practices and evolving legal and social standards" (Brown, 2016).

Even with the updated policies in place, many NFL teams have been reluctant to fully embrace the league's policy on domestic violence. This reluctance is due to the uncertainty that other teams are going to abide by the same rules, which is categorized as a form of the "prisoner's dilemma" (Kay-Phillips, 2016). Although a team owner may want to suspend or terminate the accused abuser, the team may have economic and competitive interest, that incentivizes the team to be lenient with players who may contribute considerably to team success. NFL team owners prefer to keep their discipline internal, which has led to inconsistency in disciplinary action depending on the team philosophy, player involved, and the current coach.

One recommendation to combat these inconsistencies would be to impose a standard disciplinary policy across the league to resolve the disparity in treatment of commercially valuable players (Kay-Phillips, 2016). Kay-Phillips (2016) suggests a fourstep process for dealing with NFL domestic violence cases. This process includes putting suspects on paid administrative leave, adopting the concept that the league is responsible for discipline, mandating therapy or rehabilitation for the victim and suspect, and ensuring that the changes to the domestic violence policy are codified into the next NFL Collective Bargaining Agreement.

The studies discussed in this section examined the impact of crime and bad behavior on wage and punishment in the NFL. However, none of the studies examined the impact of specific crimes such as domestic violence and sexual misconduct, which is what this study aims to do. This study explores the crime of domestic violence, which is one of the most prevalent topics discussed in today's news and one of the most controversial topics within the sports realm. In order to understand the disciplinary system within the NFL, it is important to understand how the league treats different crimes, which is why this paper narrows the focus from general crime cases to specific domestic violence cases.

Theory

This section closely follows the models used in Nichols (2010) thesis about the causation between illicit behavior and pay. In this thesis, these theories can be used to analyze the connection between domestic violence and sexual misconduct crimes and pay. I adapt the Marginal Revenue Product of Labor theory to explain how the NFL as a business optimizes its profits while dealing with illicit behaviors that tend to deter production. The Utility Maximization theory is used to explain the individual decision-making of the players.

Marginal Revenue Product of Labor

This section provides a look at how the illicit behavior of players affects the revenue of the NFL. In this model, the NFL represents the single buyer and the players represent multiple homogeneous sellers. With a single buyer and multiple homogeneous sellers, there is a possibility of a monopsony. However, free agency and player unions generate an equity of power to help combat the total control of the single buyer. Nevertheless, that fact is ignored by the model below which treats players as individual sellers. The Marginal Revenue Product of Labor (MRP_L) is defined as:

$$MRP_L = \mathrm{MR} * \mathrm{MP} \tag{1}$$

Where marginal revenue (MR) is the change in revenue resulting from the increase in output and marginal product (MP) is the additional output for each change in input.

The ultimate goal of a firm such as the NFL is to maximize its profits. Profit can be defined as:

$$\pi = TR - TC \tag{2}$$

Where profit is equal to total revenue (TR) minus total cost (TC). Total revenue can be found using the equation:

$$TR = P * Q \tag{3}$$

Where Q is the quantity of goods sold and P is the price at which those goods are sold. Total cost can be found using the equation:

$$\mathrm{TC} = \mathrm{wL} + \mathrm{rK} \tag{4}$$

Where L is the units of labor, in this case referring to labor of players, and w is the wage paid to those players, so wL is the total cost of labor. Total cost of capital (rK) is defined using K as the units of capital and r as the rate paid towards that capital. The equations and variables defined above are used to redefine the profit maximizing equation as:

$$\pi = P * Q - wL - rK \tag{5}$$

Equation (5) shows that a firm will maximize its profits if revenue is equal or greater than costs. However, as noted in the Nichols (2010) thesis, there is a need for the addition of a new cost variable (t) to represent the illicit behavior of the players while keeping the units of labor constant. The new profit maximizing equation is:

$$\pi = P * f(L, K) - wL - rK - tL \tag{6}$$

This equation accounts for the players actions off the field. The profit maximization above is derived when the first order condition is set to zero and derived with respect to L given in equation (7):

$$\frac{\partial \pi}{\partial L} = P * \frac{\partial f(\cdot)}{\partial L} - w - t = 0 \tag{7}$$

The derived profit maximization equation can be simplified to result in equation (8):

$$P * MP_L = (w + t) \tag{8}$$

The left side of the equation equals the value of the marginal product of labor (VMP_L) resulting in equation (9):

$$VMP_L = (w + t) \tag{9}$$

Given a specific $f(\cdot)$, one can rearrange equation (9) and solve for equation (10):

$$Wage = f(VMP_L, t) \tag{10}$$

The on-field statistics and illicit acts variables will be used in equation (11) to conduct the regression results for this study. The equation will be

$$Wage = f(On\ field\ statistics, cost\ of\ illicit\ behaviors) \tag{11}$$

Conclusion

This study will refer to the Marginal Revenue Product of Labor theory to show how the NFL as a business optimizes its profits with illicit behaviors, such as cases of domestic violence and sexual misconduct, that tend to deter production. This theory suggests a connection between behavior and pay, which is why this paper will use the profit maximization part of the Marginal Revenue Product of Labor theory to help guide the data and research used to test the hypothesis that there is a correlation between cases of domestic violence and sexual misconduct and changes in NFL salary contracts using equation (11).

Data and Methods

This chapter will look at the data and model used to analyze the effect of general crimes on NFL player salary contracts. For this model, the dependent variable is the adjusted salary of the players. The independent variables are divided into two categories: position-specific on-field production statistics and illicit-act variables.

Data used for the position-specific variables was previously scraped from NFL.com into Stata. This data is from the 2009-2018 NFL regular seasons, excluding 2010 due to a lack of salary data. The position-specific variables were analyzed for the following three offensive positions: quarterback, running back, and wide receiver. These positions were chosen because they are the three most significant “skilled player” offensive positions. Each position has different on-field statistics that affect their overall salary. In this study, the variables analyzed for quarterbacks are total completions, total yards, total interceptions, and passer rating. For running backs, the variables examined are total yards, total receptions, total first downs and total touchdowns. The variables for wide receivers are total yards, total receptions, and total first downs. The second part of the independent variable data is the illicit acts variable. Initially, this study focused on the specific illicit act of domestic violence but broadened the focus to general crimes due to a lack of significant domestic violence data. Consequently, the illicit acts analyzed include crimes such as DUI, assault, drug abuse, and domestic violence. Criminal data was collected from the USA Today NFL Arrest Database. The dependent variable data was found from both the USA Today NFL Salary Database and the Spotrac Salary Rankings Database.

Regression Model

Similar to Nichols (2010), this study uses an Ordinary Least Squares (OLS) regression to analyze the effect a criminal act has on an NFL player's salary. The OLS method accounts for the Classic Linear Regression Model (CLRM) assumptions. One assumption is that the error term has a constant variance, which would mean there is no heteroskedasticity. To check for heteroskedasticity for each regression, a White test was conducted. For quarterbacks, this test gave a p-value of 0.0263, showing that we reject the null hypothesis of homoskedasticity and there is heteroskedasticity. To correct for heteroskedasticity, a new regression was used accounting for standard errors and covariance. For running backs, the White test gave a p-value of 0.9923, showing that we fail reject the null hypothesis of homoskedasticity. For wide receivers, the White test gave a p-value of 0.0068, showing that we reject the null hypothesis of homoskedasticity and there is heteroskedasticity. Similar to quarterbacks, a new regression was used accounting for standard errors and covariance.

Another CLRM assumption accounted for in this study is that all independent variables are uncorrelated with the error term, otherwise there can be simultaneity between variables, omitted variable bias, or a measurement error in the independent variables. To check for this, a Breusch-Godfrey test was conducted for each position. For quarterbacks, the test resulted in a p-value of 0.994, meaning that the model has no serial correlation. For running backs, the test resulted in a p-value of 0.8387, meaning that the model has no serial correlation. For wide receivers, the test resulted in a p-value of 0.0938 at a 10% confidence interval, suggesting there may be borderline serial correlation. To correct for correlation, a Newey-West regression was used. If there is correlation, it becomes difficult to differentiate how the error term is affecting each variable individually.

Finally, a histogram of the data for each position was used to check for normality. For each position, the Jarque-Bera statistic was above 5.9, suggesting that the data is normal. In each histogram the t-statistic is not valid; however, as the sample size increases, the results will become more normal.

The following regression model is the OLS model used in this study.

$$adjsalary\_log = f\{laganycrime, lagcomp_{n-1}, lagyards_{n-1}, lagtd_{n-1}, lagint_{n-1}, lagpr_{n-1}, lagfirst_{n-1}, lagrecep_{n-1}, d11, d12, d13, d14, d15, d16, d17, d18\}$$

The regression results are used to analyze the independent variables and their connection to the dependent variable.

Variables

The dependent variable used in this model is adjsalary_log which is the variable adjsalary in logarithms. It is logged to help estimate the approximate proportional change in total adjusted salary when the independent variables change. The salary variable is adjusted to account for yearly inflation up to the most recent year (2018). To account for inflation, the salary of a player in a given year was divided by the value of the consumer price index (CPI) for that given year multiplied by the CPI of the most recent year (2018).

The independent variables that are categorized as position-specific variables used in this study are $lagcomp_{n-1}$, $lagyards_{n-1}$, $lagtd_{n-1}$, $lagint_{n-1}$, $lagpr_{n-1}$, $lagfirst_{n-1}$, and $lagrecep_{n-1}$, which are all performance variables. The time variable is seasons played, which is a dummy variable for each year played where the variable takes on a value of 1 if the player played in that specific season. For example, for the season 2011, the time variable will take a value of 1 if the player played in 2011. This is repeated for years 2011-2018. The illicit act variable is laganycrime, which is a lagged dummy variable where the variable takes on a value of 1 if a crime was committed and a 0 if no crime was committed. This variable is lagged to test for the effect it has on the player's salary from the previous year. All the variables used in this study can be found in table one alongside their descriptive statistics.

Table 1: Variable Definitions and Descriptive Statistics

Variable	Definition	M	SD
adjsalary_log	The salary for a player in a given year adjusted for inflation.	14.13006	1.278
laganycrime	The one-year lagged dummy variable for accusations of general crime. 1= if crime was committed.	.0209143	.1431187
$lagcomp_{n-1}$	The one-year lagged variable representing total completions for a given year.	135.8532	138.3996
$lagyards_{n-1}$	The one-year lagged variable representing total yards for a given year.	523.4742	873.0987
$lagtd_{n-1}$	The one-year lagged variable representing total touchdowns for a given year.	3.268736	5.953734
$lagint_{n-1}$	The one-year lagged variable representing total interceptions for a given year.	5.729117	5.803586
$lagpr_{n-1}$	The one-year lagged variable representing quarterback passer rating for a given year.	78.94057	24.24908
$lagfirst_{n-1}$	The one-year lagged variable representing total first downs for a given year.	25.43029	42.30336
$lagrecep_{n-1}$	The one-year lagged variable representing total receptions for a given year.	25.84622	27.55544

Results and Analysis

This section discusses the OLS regression results separated by position. For each position (QB, RB, and WR), a dummy variable was created where the variable takes on a value of 1 if the player is the position that is used in the regression for that specific position. For example, in the regression for quarterbacks, the variable will take a 1 if the player is the quarterback position. This will be the same for running backs and wide receivers. The table for each position displays the coefficient, t-statistic, and p-value for each variable. The regression output is used to determine the significance of the correlation between the independent variables and the adjusted salary. The p-value is used to help determine the significance of each variable. Also given is the R-squared and Adjusted R-squared for each regression, which help to explain the overall fit of the model.

Table 2: Quarterback Regression Results

Variable	Coefficient	T-Statistic	P-value
laganycrime	-0.449351	-1.101897	0.2711
$lagcomp_{n-1}$	0.005789	1.695801	0.0906
$lagyards_{n-1}$	-0.0000274	-0.095678	0.9238
$lagint_{n-1}$	-0.023853	-1.293145	0.1966
$lagpr_{n-1}$	0.011379	4.138095	0.000
N	474		
R-Squared	0.304205		
Adj. R-Squared	0.284541		

The results for quarterback performance variables show there is little to no correlation between committing a crime and the next year's salary. This insignificance is due to a lack of players who commit crime relative to total number of players observed. In this study, there were a total of 474 NFL quarterbacks observed and only 5 who committed a crime. The variables for completions, yards, and interceptions are also insignificant, which is due to a lack of specificity with each variable targeting the specific position. The most significant variable showing little effect on the salary is the passer rating of the quarterback. This is somewhat significant because the p-value is 0.000 which is less than 0.05 and the t-statistic is the highest at 4.14.

Table 3: Running Back Regression Results

Variable	Coefficient	T-Statistic	P-Value
laganycrime	-0.119852	-0.222161	0.8245
$lagfirst_{n-1}$	-0.043864	-1.283418	0.2012
$lagrecep_{n-1}$	-0.007016	-0.371887	0.7105
$lagyards_{n-1}$	0.00383	2.396557	0.0177
$lagtd_{n-1}$	-0.041528	-0.560826	0.5757
N	176		
R-Squared	0.2139		
Adj. R-Squared	0.2113		

The results for running back performance variables show that there is no correlation between committing a crime and salary. While there is a relatively significant negative coefficient for the crime variable, the p-value and t-statistic are insignificant, invalidating the coefficient found. Similar to quarterbacks, this insignificance is due to a lack of players committing crimes relative to players observed. In this study, there were 176 running backs observed and only 27 were accused of committing a crime. Due to a lack of specificity per position, the variables for total receptions, total first downs, and total touchdowns are insignificant. The only variable that is remotely significant is the total yards variable showing a p-value of 0.0177; however, the coefficient is only 0.00383, which is not very significant.

Table 4: Wide Receiver Regression Results

Variable	Coefficient	T-Statistic	P-Value
laganycrime	-0.043536	-0.287321	0.7739
$lagrecep_{n-1}$	-0.003144	-0.503508	0.6147
$lagyards_{n-1}$	-0.0000492	-0.095472	0.924
$lagfirst_{n-1}$	0.037951	3.355332	0.0008

N	1260		
R-Squared	0.238775		
Adj. R-Squared	0.231449		

The results for wide receivers are extremely similar to the results of the running back regression in that while the coefficient for the crime variable shows negative significance, the p-value proves that it is instead insignificant. As was the case for running backs and quarterbacks, this insignificance is due to the lack of crimes committed relative to the number of players observed. In this study, there were 1,260 players observed and only 24 committed a crime. Again, the significant variable in this regression is the total first down with a p-value of 0.0008.

In this study, the insignificance of the regression results is due to both a lack of sufficient data of players who commit crimes and a lack of variable specificity towards each position. Insignificance may also be because salaries are contractually determined and if a player is not cut or does not have a contract that penalizes him for bad behavior, his salary will not be impacted. However, through this insignificance, it can be concluded that if a player commits a crime, it is likely that there will be no repercussions from the NFL regarding salary. While players may receive minimal punishment such as probation, paying a fine, or even a several days suspension, it is more common that the charges will be dropped, and player will face no consequences. This absence of punishment is disturbing in itself, but even more so when looking at the specific cases of domestic violence crimes.

Conclusion

This study continued previous research looking into the effect of crime on wage in the NFL by Ryan Nichols (2010). However, unlike previous studies, the initial focus of this study was the specific crime of domestic violence and how it effects NFL salaries. After collecting both domestic violence crime data, other general crime data, and running the OLS model, the domestic violence data was insignificant. This insignificance was due to a lack of players committing a domestic violence crime relative to the total number of players observed in this study. Subsequently, the study shifted focus from domestic violence crimes specifically and grouped those crimes with the other general crime data. Another reason for the insignificance was a lack of specific data targeted towards each position. This study only looked at data for running backs, quarterbacks, and wide receivers and used data from NFL.com that was previously scraped into Stata. Since this data worked with a limited number of position-specific variables, the variables that were used resulted as insignificant.

One significant conclusion can be drawn from the insignificance of the regression runs. It can be concluded that if a quarterback, running back, or wide receiver commits a crime as a player in the NFL, he will most likely not take a hit to his overall salary. Similar to the inconsistency in discipline for domestic violence across the National Football League, the nonexistent impact on the players' salaries is another example of an inconsistency within the NFL.

When collecting data for this study, running backs and wide receivers committed most of the crimes with quarterbacks committing very few. One theory behind this difference in crime committed would be the impact of race on accusations of crime. For example, players in the quarterback position are predominately white and have been accused of significantly fewer crimes than running backs and wide receivers. Exploring the factor of race on criminal accusations would be an impactful model to use to conduct further research around the subject of crime in the NFL. This study could investigate the correlation between crimes committed in each position and the race of the majority of the players of that specific position. While this study may yield similar results in that there is no impact on the salaries of the players, it is important to continue to explore the different reasons behind the inconsistency of the disciplinary action across the National Football League.

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Appendix

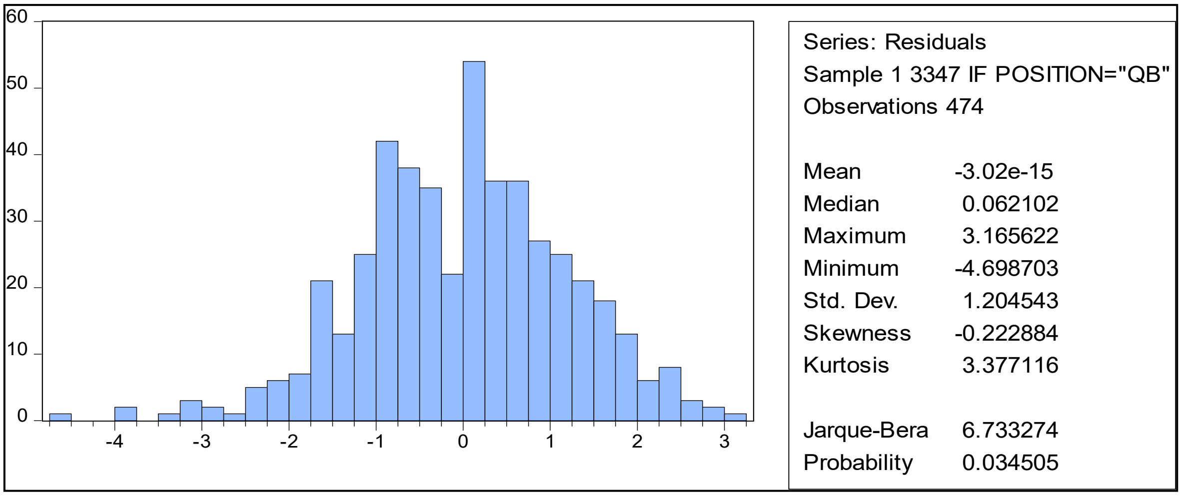
Model 1. Regression results for quarterbacks: The dependent variable is the log of NFL player's annual salary adjusted for inflation. The independent lagged variables include: total completions, total yards, total interceptions, passer rating, a dummy variable of any crime, and a dummy variable for each season played for seasons 2011-2018 (d11-d18).

Dependent Variable: ADJSALARY_LOG
Included observations: 474
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.94002	0.338706	41.15668	0
LAGANYCRIME	-0.44935	0.407798	-1.1019	0.2711
LAGCOMP	0.005789	0.003414	1.695801	0.0906
LAGYARDS	-2.74E-05	0.000286	-0.09568	0.9238
LAGINT	-0.02385	0.018446	-1.29315	0.1966
LAGPR	0.011379	0.00275	4.138095	0
D11	-0.32804	0.319897	-1.02545	0.3057
D12	-0.43082	0.307251	-1.40216	0.1615
D13	-0.69526	0.307594	-2.26032	0.0243
D14	-0.57523	0.31366	-1.83393	0.0673
D15	-0.69262	0.315244	-2.19708	0.0285
D16	-0.22674	0.31803	-0.71297	0.4762
D17	-0.6008	0.30433	-1.97419	0.049
D18	-0.3743	0.326416	-1.14671	0.2521

R-squared	0.304205	Mean dependent var	15.00296
Adjusted R-squared	0.284541	S.D. dependent var	1.444048
S.E. of regression	1.221445	Akaike info criterion	3.267037
Sum squared resid	686.2866	Schwarz criterion	3.389942
Log likelihood	-760.288	Hannan-Quinn criter.	3.315374
F-statistic	15.47033	Durbin-Watson stat	2.009499
Prob(F-statistic)	0	Wald F-statistic	24.84584
Prob(Wald F-statistic)	0		

Figure 1. Histogram test for normality for quarterbacks.



Model 2. White test to test for heteroskedasticity for quarterbacks:

Heteroskedasticity Test: White

F-statistic	1.93E+00	Prob. F(13,460)	0.0247
Obs*R-squared	24.57162	Prob. Chi-Square(13)	0.0263
Scaled explained SS	27.5051	Prob. Chi-Square(13)	0.0106

Model 3. Breusch-Godfrey test for serial correlation for quarterbacks:

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.014981	Prob. F(3,457)	0.9975
Obs*R-squared	0.046611	Prob. Chi-Square(3)	0.9974

Model 4. Regression results correcting for heteroskedasticity accounting for standard errors and covariance.

Test Equation:
Dependent Variable: RESID^2
Included observations: 474
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.26766	0.352065	3.600645	0.0004
LAGANYCRIME^2	-0.3374	0.530919	-0.635505	0.5254
LAGCOMP^2	3.19E-07	8.86E-06	0.035964	0.9713
LAGYARDS^2	-7.89E-08	6.19E-08	-1.274054	0.2033
LAGINT^2	0.001226	0.000871	1.408694	0.1596
LAGPR^2	7.64E-05	3.70E-05	2.062044	0.0398
D11^2	-0.00043	0.495305	-0.00086	0.9993
D12^2	-0.29902	0.352684	-0.847827	0.397
D13^2	-0.18568	0.374745	-0.495482	0.6205
D14^2	-0.02769	0.428825	-0.064561	0.9486
D15^2	0.101195	0.442666	0.228603	0.8193
D16^2	0.073192	0.471426	0.155256	0.8767
D17^2	-0.25017	0.340974	-0.733695	0.4635
D18^2	0.329436	0.415313	0.793224	0.4281

R-squared	0.051839	Mean dependent var	1.447862
Adjusted R-squared	0.025043	S.D. dependent var	2.234658
S.E. of regression	2.206499	Akaike info criterion	4.449782
Sum squared resid	2239.573	Schwarz criterion	4.572687
Log likelihood	-1040.6	Hannan-Quinn criter.	4.498119
F-statistic	1.934585	Durbin-Watson stat	2.643157
Prob(F-statistic)	0.024692		

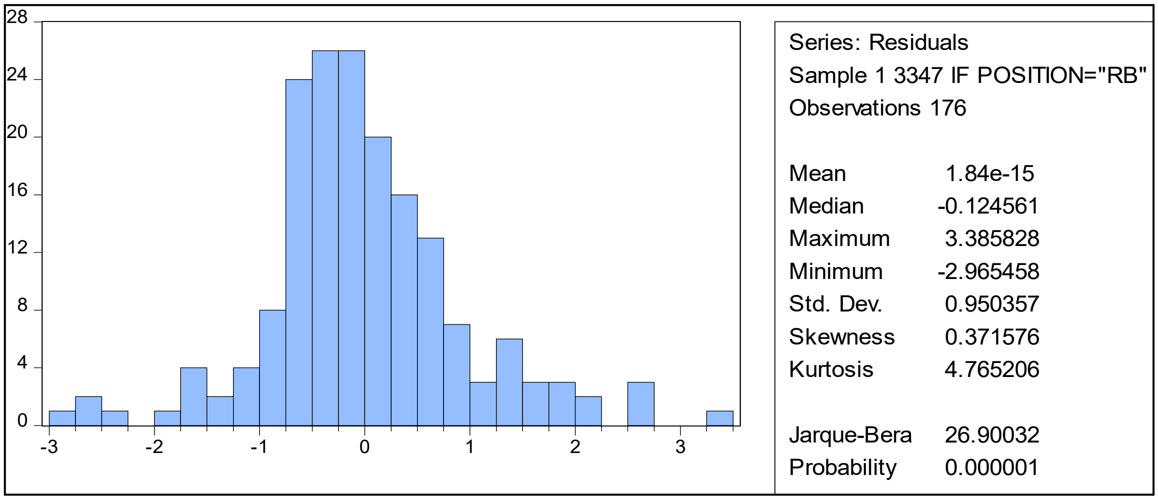
Model 5. Regression results for running backs: The dependent variable is the log of NFL player's annual salary adjusted for inflation. The independent lagged variables include: total completions, total yards, total interceptions, passer rating, a dummy variable of any crime, and a dummy variable for each season played for seasons 2011-2018 (d11-d18).

Dependent Variable: ADJSALARY_LOG
Included observations: 176

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.59075	0.158848	85.55794	0
LAGANYCRIME	-0.11985	0.539482	-0.22216	0.8245
LAGFIRST	-0.04386	0.034177	-1.28342	0.2012
LAGRECEP	-0.00702	0.018865	-0.37189	0.7105
LAGYARDS	0.00383	0.001598	2.396557	0.0177
LAGTD	-0.04153	0.074048	-0.56083	0.5757
D11	-0.34432	0.296671	-1.16063	0.2475
D12	-0.51585	0.2911	-1.77207	0.0783
D13	-0.75382	0.276144	-2.72982	0.007
D14	-0.24317	0.335267	-0.72529	0.4693
D15	-0.24235	0.295171	-0.82104	0.4128
D16	-0.55843	0.257528	-2.16843	0.0316
D17	0.027075	0.284128	0.095291	0.9242
D18	-0.06057	0.296852	-0.20405	0.8386

R-squared	0.136446	Mean dependent var	13.49986
Adjusted R-squared	0.067148	S.D. dependent var	1.022685
S.E. of regression	0.987753	Akaike info criterion	2.889435
Sum squared resid	158.0562	Schwarz criterion	3.141632
Log likelihood	-240.27	Hannan-Quinn criter.	2.991725
F-statistic	1.968983	Durbin-Watson stat	1.984336
Prob(F-statistic)	0.026383		

Figure 2. Histogram test for normality for running backs.



Model 6. White test to test for heteroskedasticity for running backs:

Heteroskedasticity Test: White

F-statistic	0.503534	Prob. F(58,117)	0.9978
Obs*R-squared	35.15663	Prob. Chi-Square(58)	0.9923
Scaled explained SS	5.61E+01	Prob. Chi-Square(58)	0.5472

Model 7. Breusch-Godfrey test for serial correlation for running backs:

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.037914	Prob. F(1,161)	0.8459
Obs*R-squared	0.041436	Prob. Chi-Square(1)	0.8387

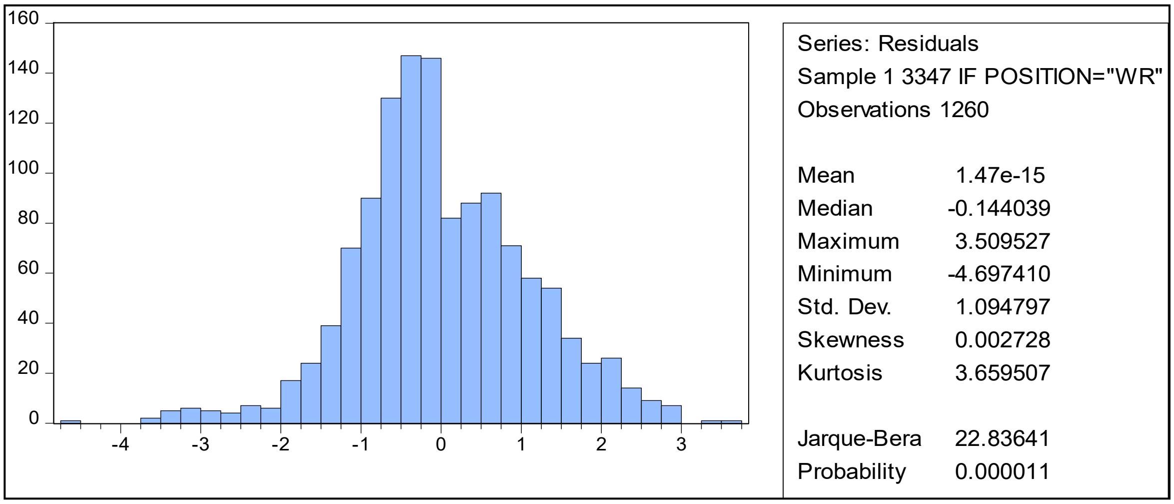
Model 8. Regression results for wide receivers: The dependent variable is the log of NFL player's annual salary adjusted for inflation. The independent lagged variables include: total completions, total yards, total interceptions, passer rating, a dummy variable of any crime, and a dummy variable for each season played for seasons 2011-2018 (d11-d18).

Dependent Variable: ADJSALARY_LOG
Included observations: 1260
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 8.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.84313	0.11811	117.2057	0
LAGANYCRIME	-0.04354	0.151523	-0.28732	0.7739
LAGRECEP	-3.14E-03	0.006244	-0.50351	0.6147
LAGYARDS	-4.92E-05	0.000515	-0.09547	0.924
LAGFIRST	0.037951	0.011311	3.355332	0.0008
D11	-0.22575	0.15488	-1.45757	0.1452
D12	-0.30307	0.14411	-2.10304	0.0357
D13	-0.50147	0.135942	-3.68883	0.0002
D14	-0.35511	0.146859	-2.41806	0.0157
D15	-0.34281	0.142519	-2.40533	0.0163
D16	-0.46524	0.166188	-2.79947	0.0052
D17	-0.35705	0.147113	-2.42707	0.0154
D18	-0.30663	0.144142	-2.12726	0.0336

R-squared	0.238775	Mean dependent var	14.0805
Adjusted R-squared	0.231449	S.D. dependent var	1.254807
S.E. of regression	1.100052	Akaike info criterion	3.038856
Sum squared resid	1509.014	Schwarz criterion	3.091876
Log likelihood	-1901.48	Hannan-Quinn criter.	3.058781
F-statistic	32.59566	Durbin-Watson stat	2.111936
Prob(F-statistic)	0	Wald F-statistic	33.62554
Prob(Wald F-statistic)	0		

Figure 3. Histogram test for normality for wide receivers.



Model 9. White test to test for heteroskedasticity of wide receivers:

Heteroskedasticity Test: White

F-statistic	2.307132	Prob. F(12,1247)	0.0066
Obs*R-squared	2.74E+01	Prob. Chi-Square(12)	0.0068
Scaled explained SS	3.56E+01	Prob. Chi-Square(12)	0.0004

Model 10. Breusch-Godfrey test for serial correlation for wide receivers:

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.782112	Prob. F(1,1246)	0.0956
Obs*R-squared	2.807104	Prob. Chi-Square(1)	0.0938

Model 11. Regression results correcting for heteroskedasticity accounting for standard errors and covariance.

Test Equation:
Dependent Variable: RESID^2
Included observations: 1260
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.037216	0.124469	8.333126	0.00E+00
LAGANYCRIME^2	-0.423664	0.163418	-2.59252	0.0096
LAGRECEP^2	8.32E-05	6.65E-05	1.250072	0.2115
LAGYARDS^2	-2.58E-07	5.69E-07	-0.45298	0.6506
LAGFIRST^2	-3.36E-05	0.000222	-0.151	0.88
D11^2	-0.207008	0.165049	-1.25422	0.21
D12^2	-0.131992	0.165475	-0.79766	0.4252
D13^2	-0.09167	0.190125	-0.48216	0.6298
D14^2	0.027203	0.202499	0.134334	0.8932
D15^2	0.101702	0.199827	0.508952	0.6109
D16^2	0.64124	0.265701	2.41339	0.0159
D17^2	0.424515	0.214317	1.980782	0.0478
D18^2	0.166459	0.194628	0.855269	0.3926

R-squared	0.02172	Mean dependent var	1.19763
Adjusted R-squared	0.012305	S.D. dependent var	1.95387
S.E. of regression	1.941811	Akaike info criterion	4.175383
Sum squared resid	4701.974	Schwarz criterion	4.228403
Log likelihood	-2617.491	Hannan-Quinn criter.	4.195307
F-statistic	2.307132	Durbin-Watson stat	1.885668
Prob(F-statistic)	0.00656		